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TECHNOLOGIES
DEEPSECURITY: APPLYING
DEEP LEARNING TO
HARDWARE SECURITY
QUEEN'S
UNIVERSITY
BELFAST
ESTP1845

DeepSecurity: Applying Deep Learning to Hardware Security

Overall Goal

To investigate the use of Deep Learning for security verification in EDA tools, specifically in relation to *Hardware Trojan detection* and *Side channel analysis* to allow non-security experts to receive feedback on how to improve the security of their designs prior to fabrication.

Rambus Cryptography Research

riscure

BAE SYSTEMS

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Hardware Trojan Detection

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Detecting Hardware Trojans – IC Production Stage

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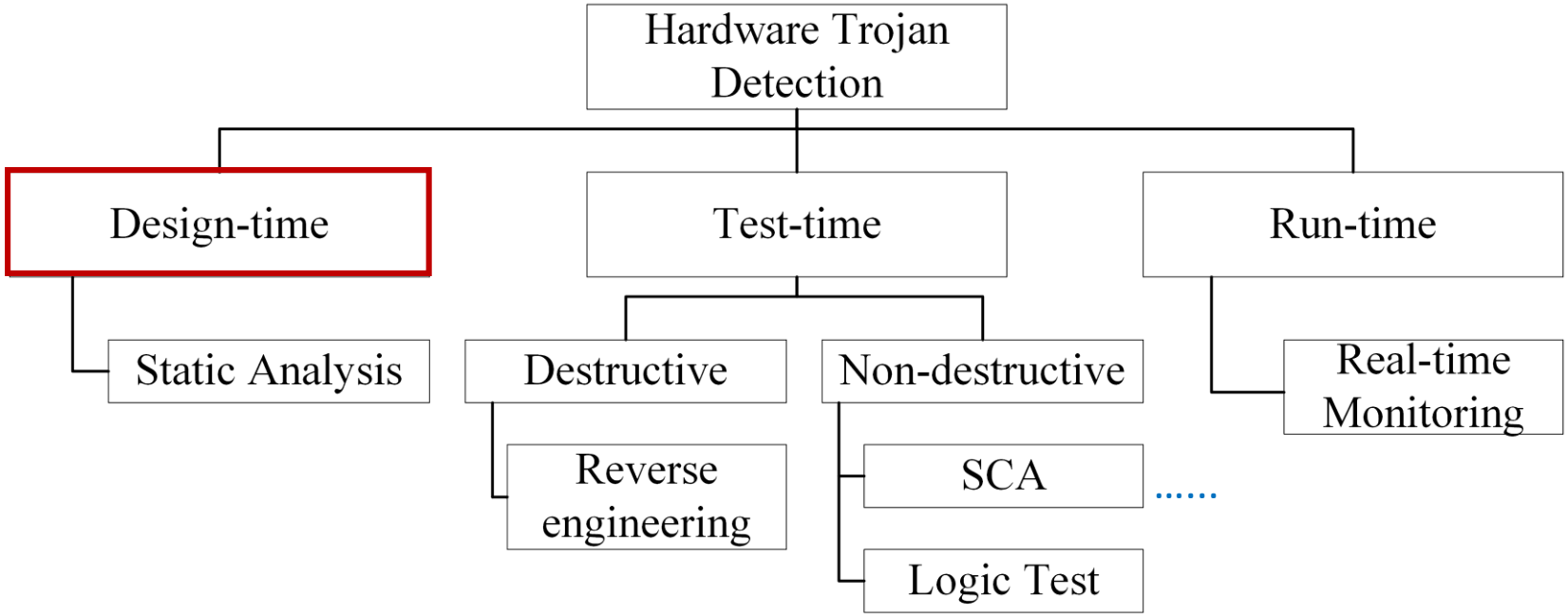


Plan And Progress

Paper:
"An Improved Automatic Hardware Trojan Generation Platform" ISVLSI 2019, July 2019
" A Novel Feature Extraction Strategy for Hardware Trojan Detection " ISCAS 2020, (Submitted)

- ❑ Highly configurable in HT types;
- ❑ Triggered under rare conditions;
- ❑ HT-infected circuits with reports

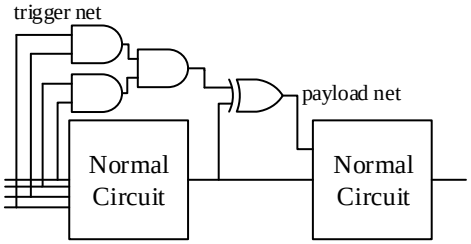
- ❑ Netlist parsing;
- ❑ Netlist block (in *N* logic levels);
- ❑ Trojan's structural features;
- ❑ Dynamic features (Switching activity)

- ❑ Unsupervised machine learning (K-means Clustering);
- ❑ Supervised machine learning (SVM);
- ❑ Deep Learning (under development)

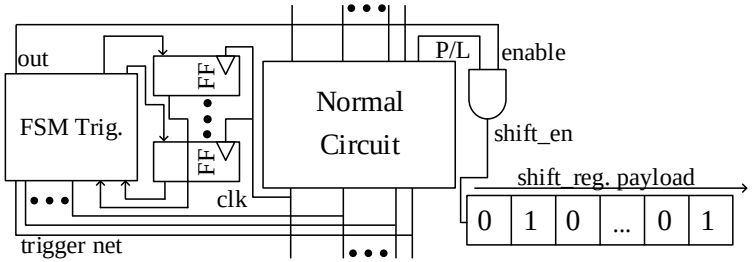
*SVM: Support Vector Machine

An Improved Automatic Hardware Trojan Generation Platform

Generated HT benchmark samples:



(a) Combinational Trojan with functional error payload



(b) FSM based sequential Trojan with a SHIFT based leakage circuit

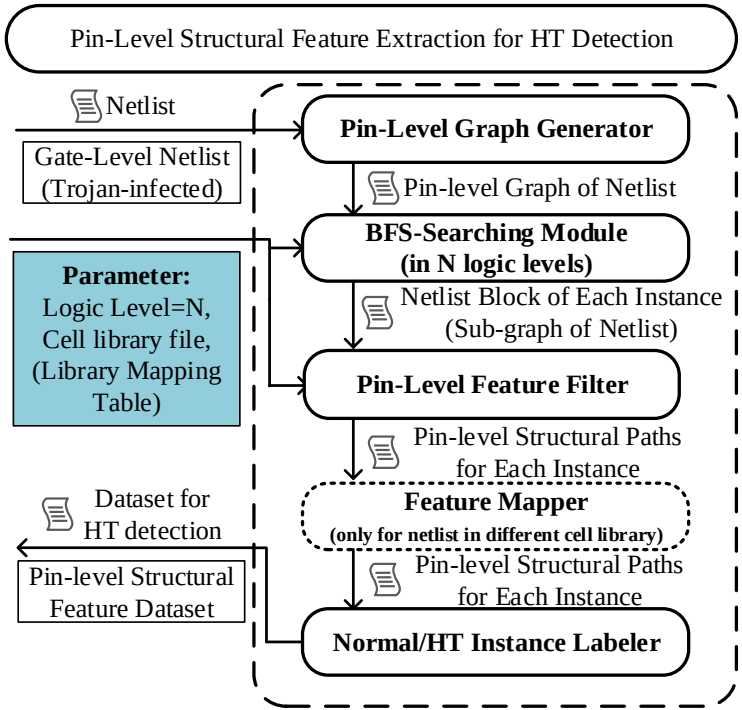
When compared with the COTD detection results from [1], who proposed a dynamic Hardware Trojan benchmark.

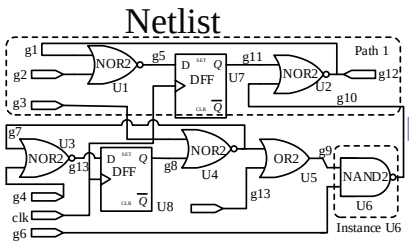
TABLE I
COMPARISON OF COTD-BASED HT DETECTION RESULTS

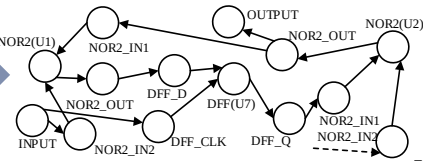
Benchmarks	Trigger Conditon (Rare/Total)	Type	HTs in [1]		Generated HTs [2]	
			FPR(%)	FNR(%)	FPR(%)	FNR(%)
s13207-c5_6	5/6	comb	25	0	0.39	23
s13207-s5_6	5/6	seq	0.11	0	0.41	19
s15850-c5_6	5/6	comb	27	0	12	25
s15850-s5_6	5/6	seq	0.09	0	0.11	17
s35932-c5_6	5/6	comb	60	0	15	33
s35932-s5_6	5/6	seq	0.08	0	0.03	20

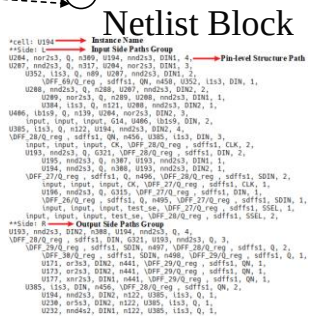
[1] J. Cruz, Y. Huang, P. Mishra, and S. Bhunia, "An automated configurable trojan insertion framework for dynamic trust benchmarks," in Proc. Design, Automation Test in Europe Conf. Exhibition, March 2018

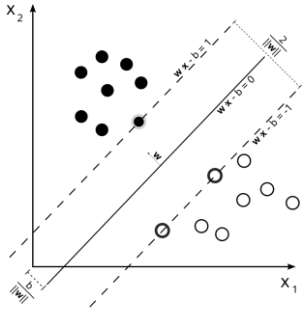
A Novel Feature Extraction Strategy for Hardware Trojan Detection







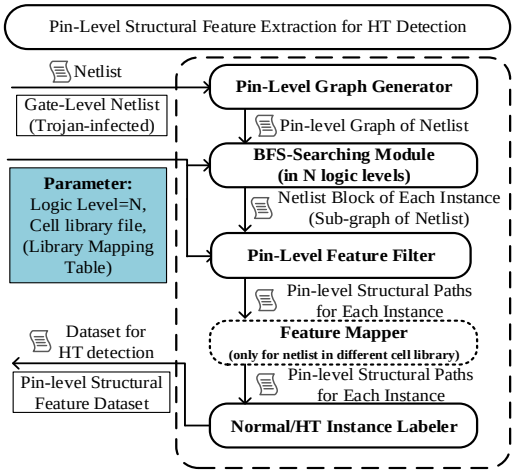




Next Steps

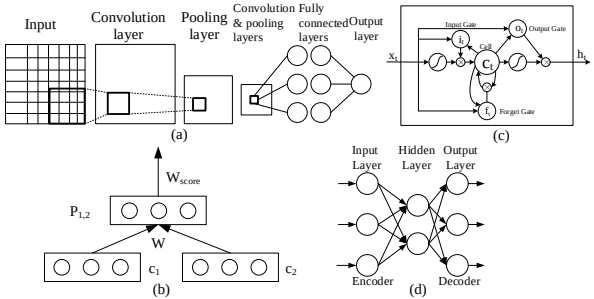
- Deep Learning-based HT detection model
- Testing:
  - Training Set: HT-infected benchmarks generated from our HT generation platform.
  - Testing Set: open-sourced HT benchmarks.

HT-infected Netlists



Novel Feature Extraction Program

HT Feature Traces



Deep Learning Model

Applying Deep Learning to Side-channel Analysis

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Context and motivation

- Deep learning shows potential in improving side-channel analysis.
- Available deep learning models are not really designed for side-channel attacks.
- Evaluating DL-based SCA attacks and understanding the leakage that allows successful attacks can be used to improve physical attack countermeasures for cryptographic implementations.

ASCAD database

E. Prouff *et al.* Study of deep learning techniques for SCA and Introduction to ASCAD Database, Cryptology ePrint, Report 2018/053

- ASCAD database experiments
  - 2nd order masked AES-128 implementation on ATMega processor
  - Traces are synchronized and slightly de-synchronized
- ASCAD database with FIXED key
  - 50,000 traces for learning (50,000 traces for single key)
  - 10,000 traces for attacking, 700 samples per trace
- ASCAD database with VARIABLE key
  - 200,000 traces for learning (781 traces per key in average)
  - 100,000 traces for attacking, 1,400 samples per trace

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Models

- Attacking model: output value of 3rd Sbox at 1st round

$$Sbox_{out}[3] = Sbox(Plaintext[3] \oplus Key[3])$$

- Proposed Deep Learning models
  - Convolutional Neural Network
  - Considered general knowledge in Side-channel analysis
  - Target generic AES implementation (regardless of countermeasure used).
  - Different convolutional filter kernel sizes
- Reference models (in ASCAD database)
  - First order template model
  - First order Multi Layer Perceptron (MLP)
  - Multi Layer Perceptron with input batch normalization
  - VGG16 based CNN

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Assumption of attacker

- Attacker can profile plaintext and/or ciphertext
- Attacker can profile keys on the device
- Attacker does not know specific AES implementation details but understands that the designer may or may not have applied countermeasures e.g time shifting, 1st or high order masking, dual-rail logic, etc.

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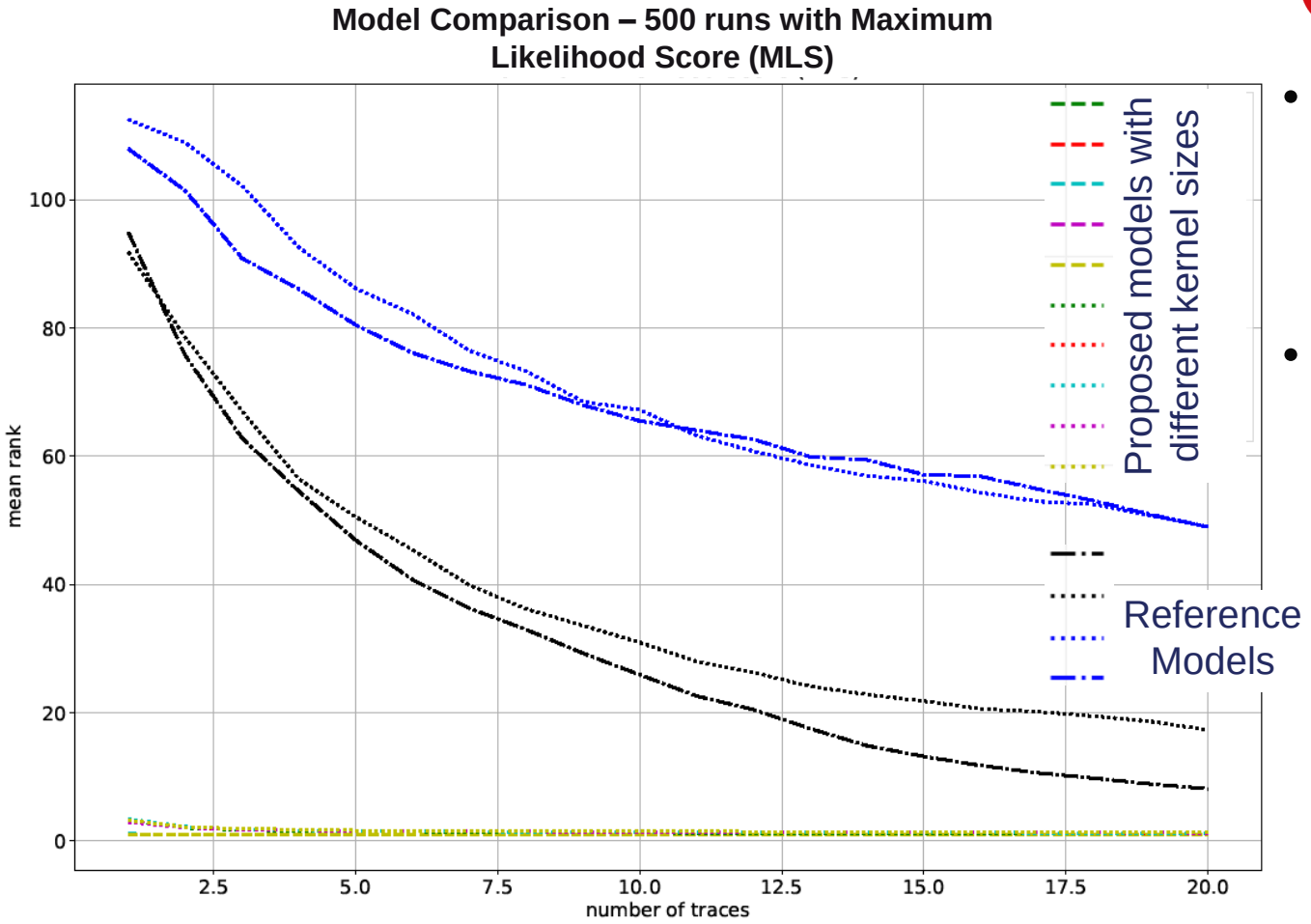
Model Development & Evaluation methods

- Use TensorFlow library for DL models

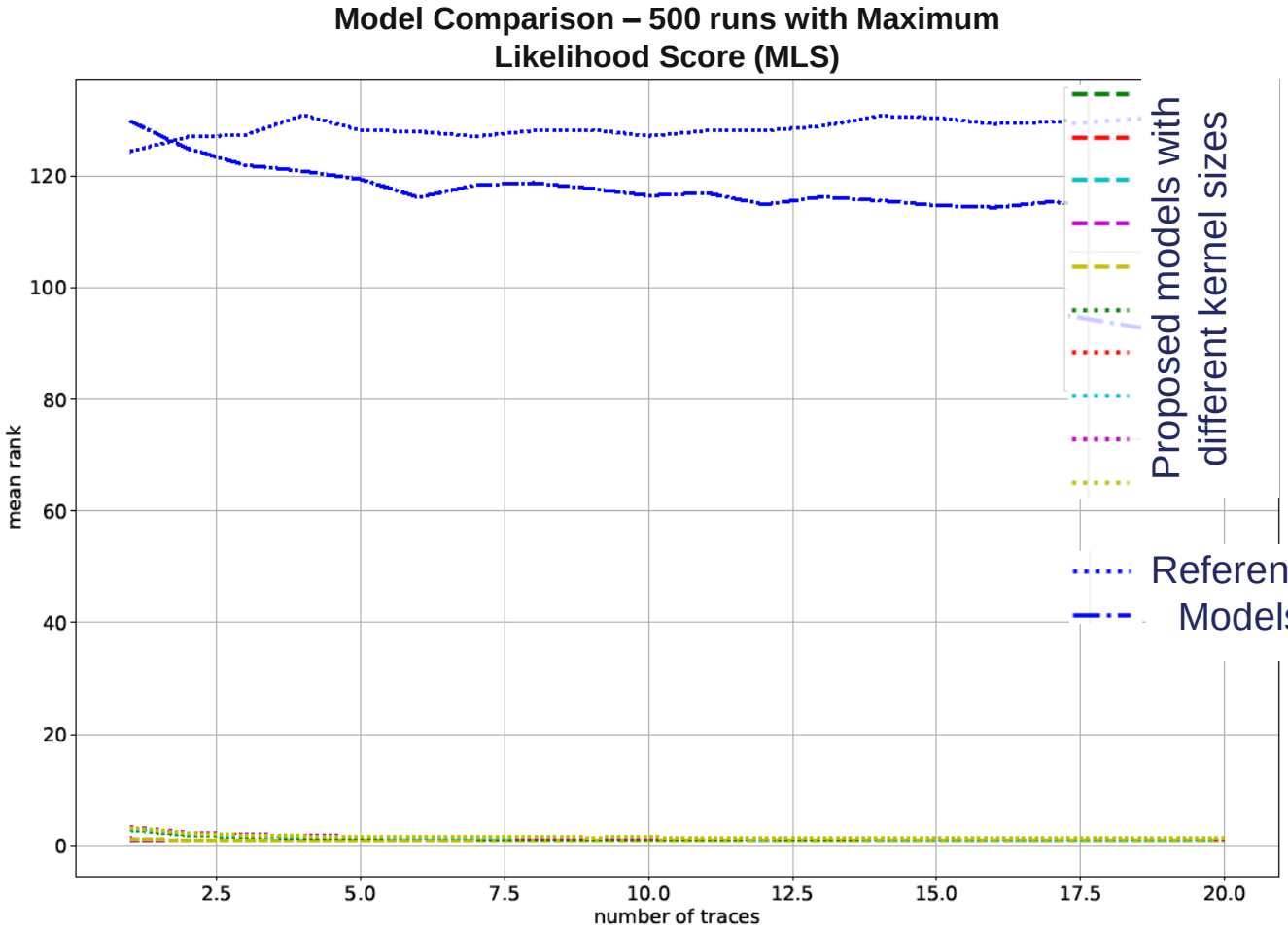
- Cross evaluation
  - Training on synchronized profile data and attacking on desynchronized attack data on the same database
  - Training on desynchronized profile data and attacking on synchronized attack data on the same database

Results for Fixed key, synchronized data



- Improves upon reference ML models (shown in blue & black)
- Our models are able to find correct sub key with a single trace

Results for Fixed key, desynchronized data



- Improves upon reference ML models (blue lines)
- All our models are able to find correct sub key within single traces

Results for Fixed key, cross evaluation

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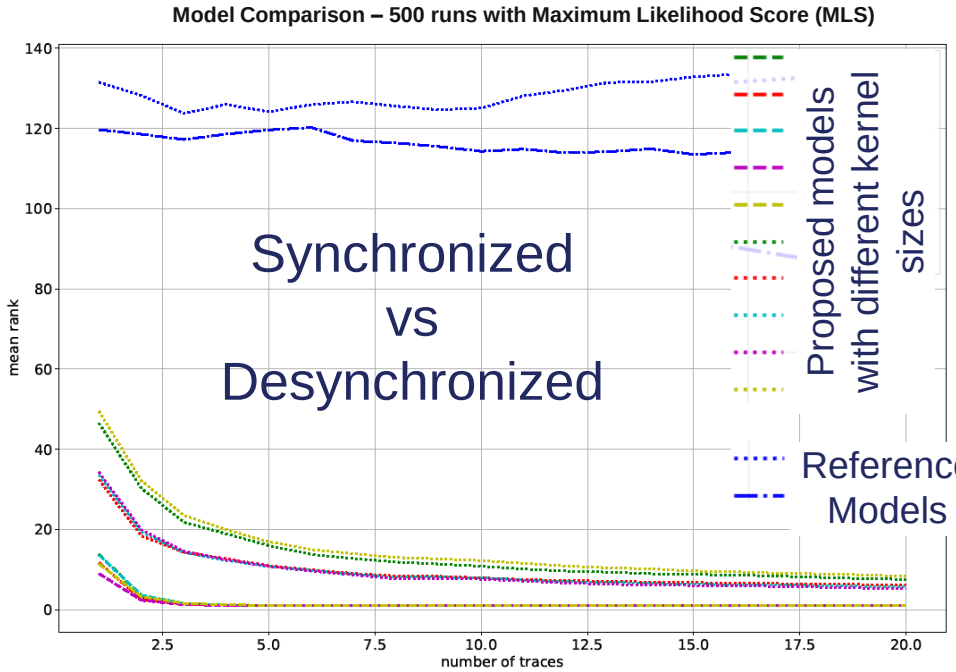

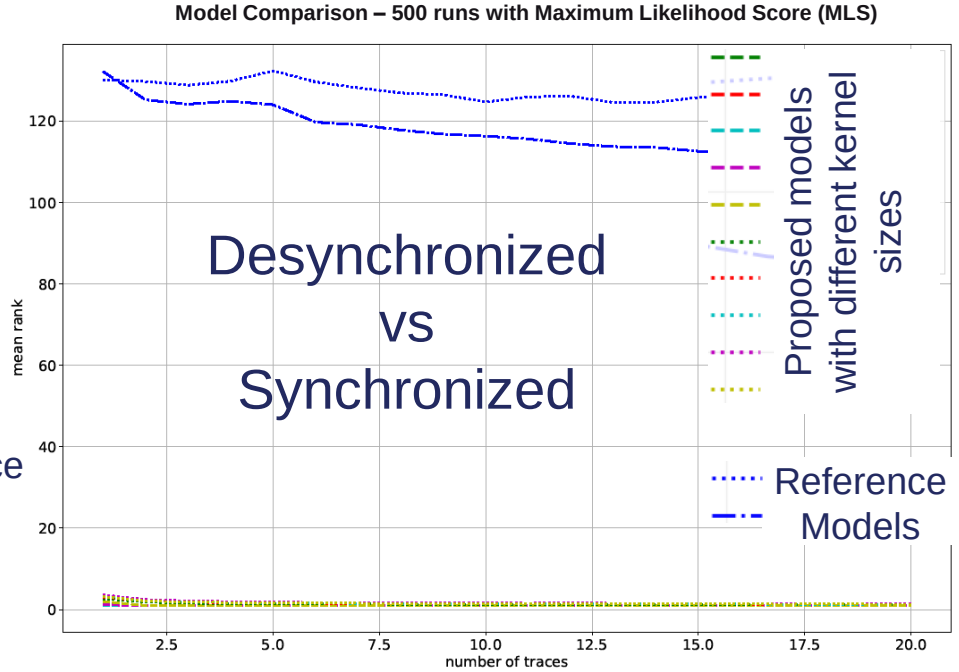

- Decrease in performance of models is observed when trained on synchronized data to attack desynchronized data
- No change observed when models trained on desynchronized data to attack synchronized data

Results for Variable key, synchronized data

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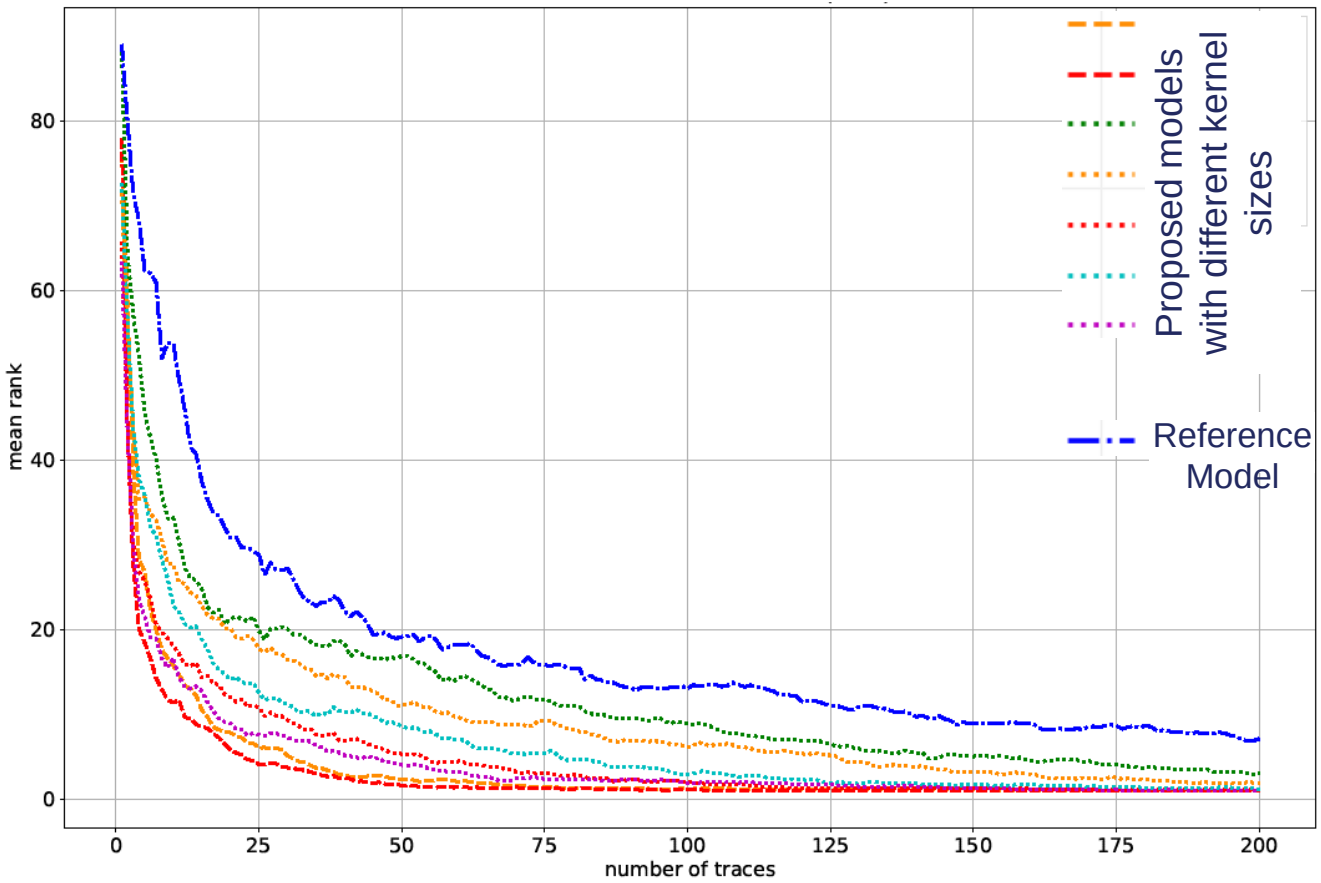

- Improves upon reference ML models (blue lines)
- Our CNN models are successful - achieve a key rank of 2 with 50 traces (2^{16} = 65,536 additional brute force attack required)

Results for Variable key, desynchronized data

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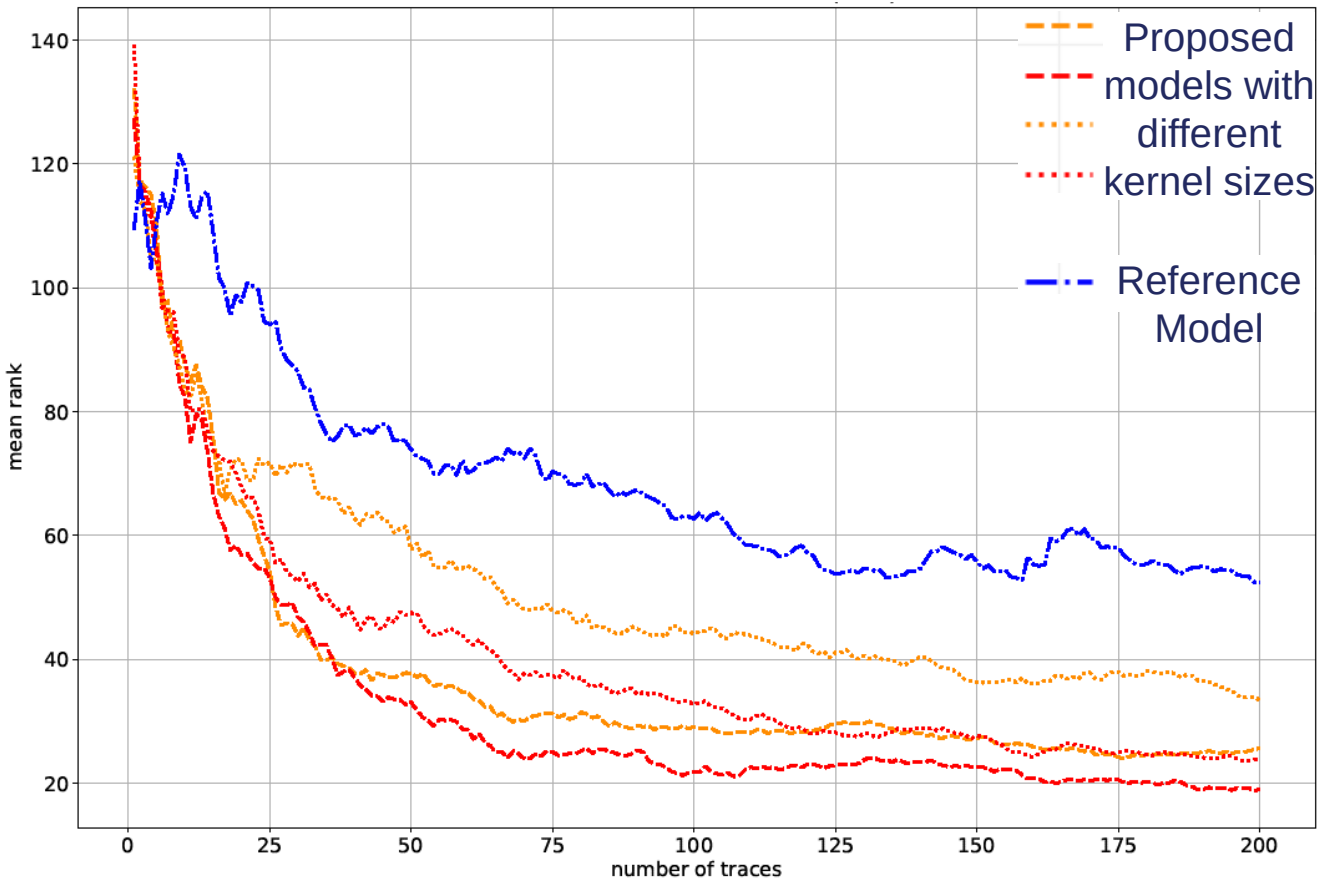
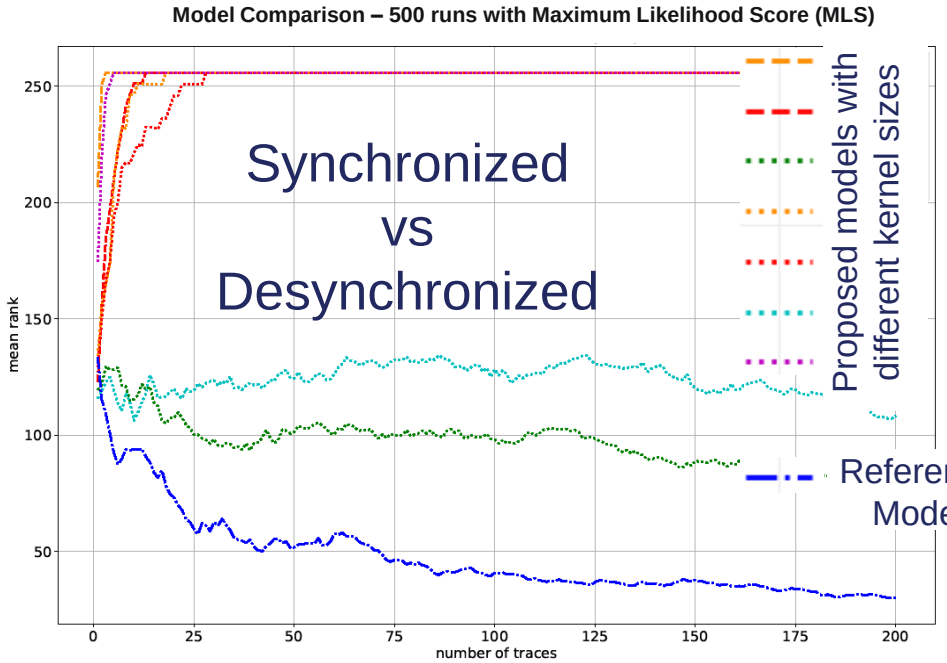
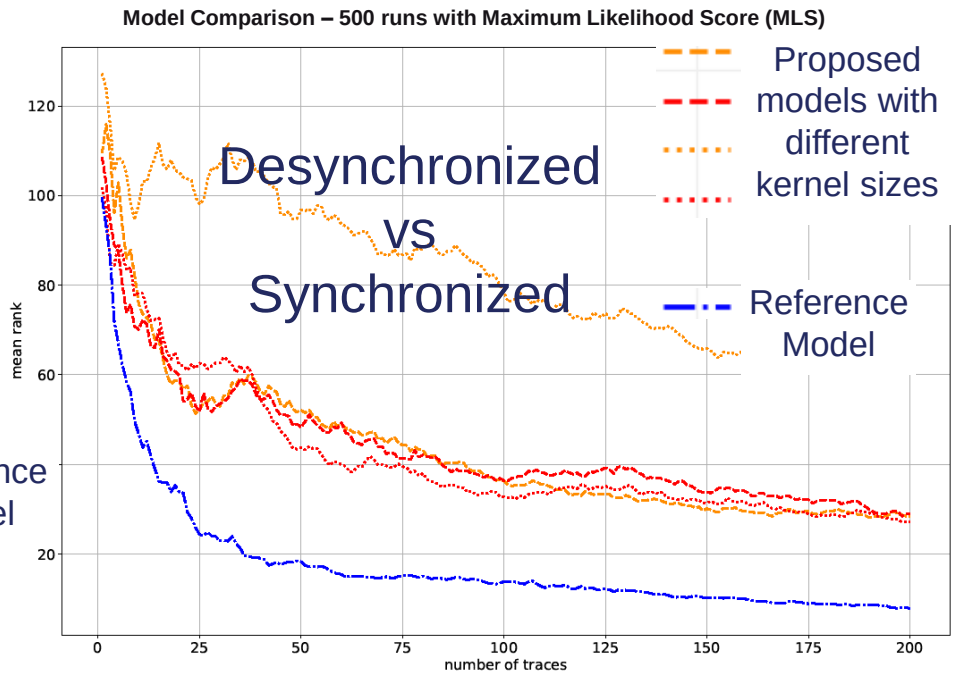


- Improves upon reference ML models (blue lines)
- Our CNN models achieve key rank 20 with 100 traces

Results for Variable key, cross evaluation





- Decrease in performance of proposed models observed in both situations
- May be due to small no. of traces available per sub key?

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Next steps

- Understand observed results in cross-evaluation attack for a variable key
- Application of proposed model to different databases, and different hardware based countermeasures, e.g. dual-rail logic approaches.
- Understand leakage that makes DL attacks possible in order to build stronger countermeasures.

Thank you